

# **Machine intelligence**

**7<sup>th</sup> lecture**

**Widrow-Hoff learning and  
Delta Rule learning**

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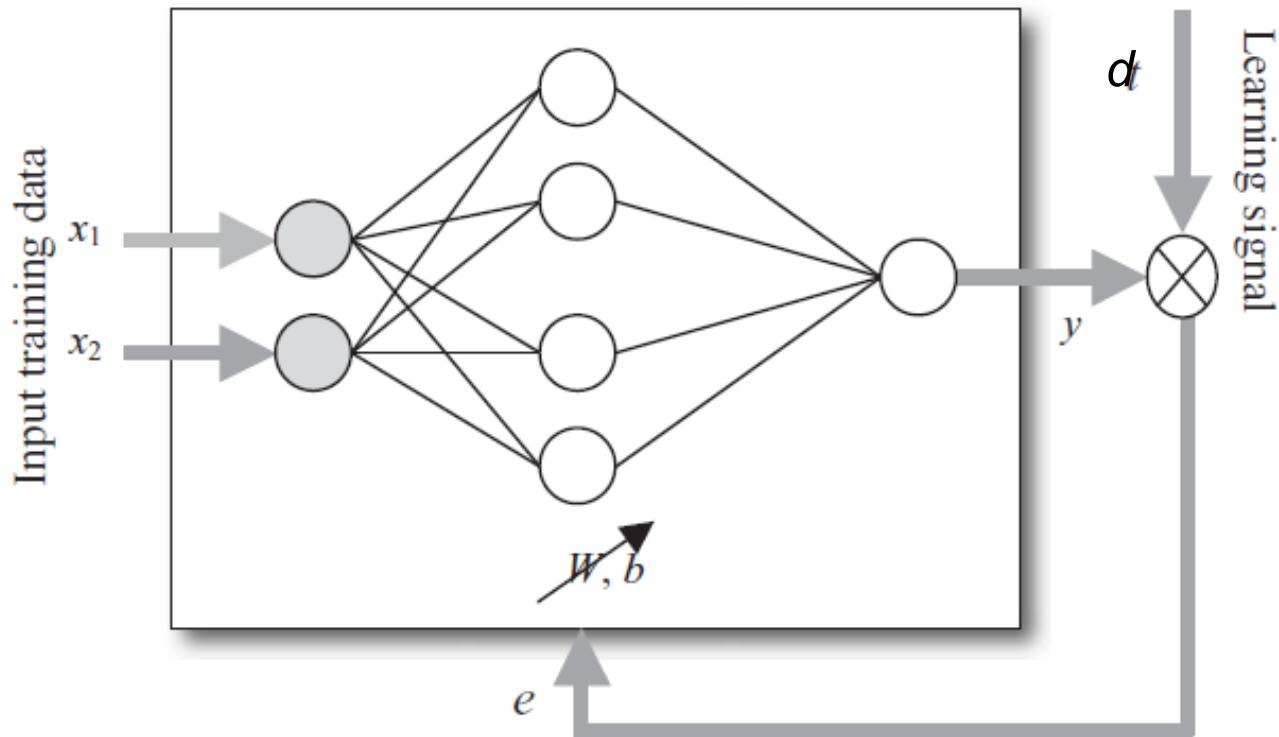


# OUTLINE

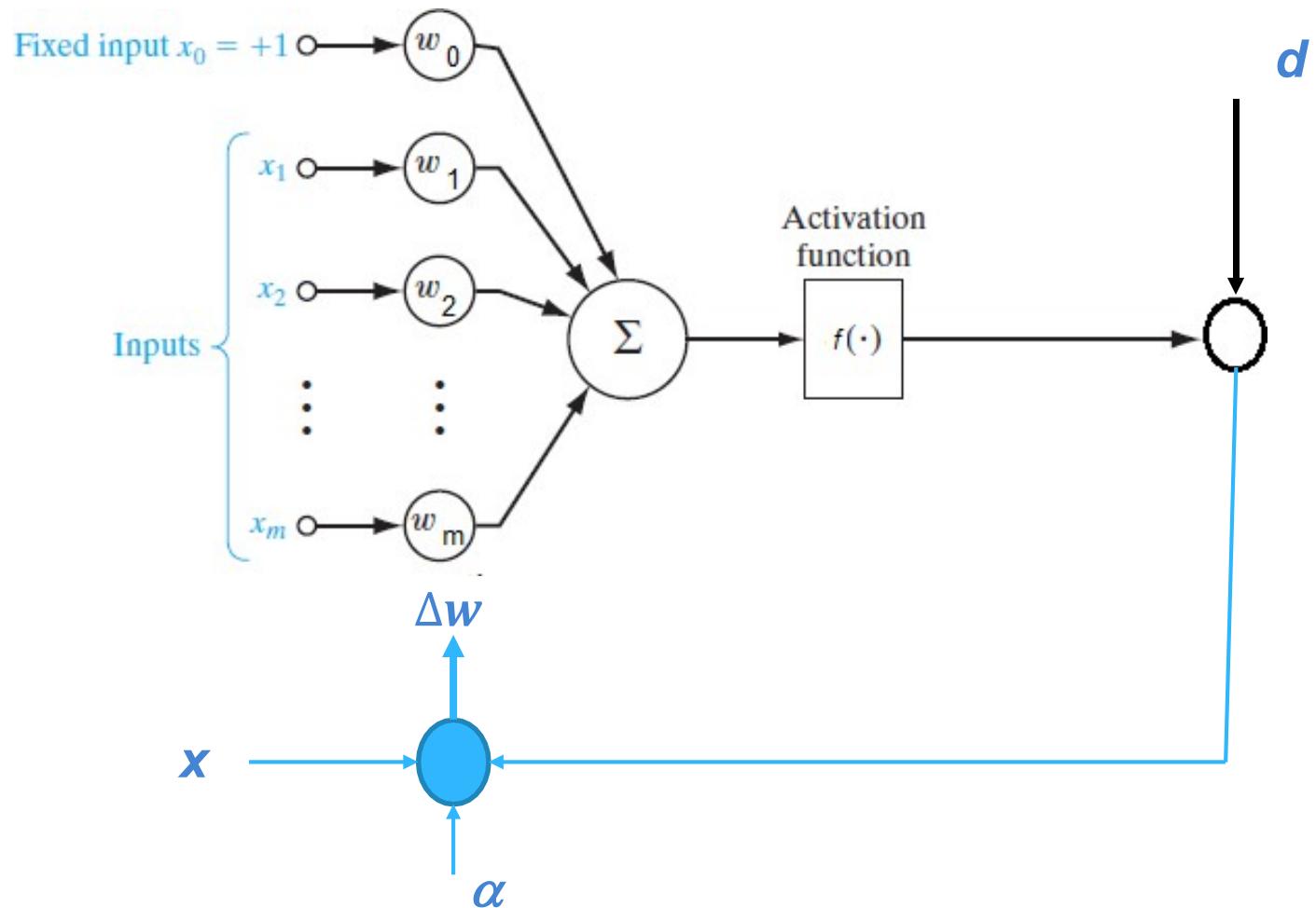
- Widrow-Hoff Algorithm
- Perceptron example
- Delta Rule Learning (one neuron)
- Example
- MATLAB example
- Delta Rule Learning (multi-neurons)



# Supervised Learning



# WIDROW-HOFF LEARNING ALGORITHM



# WIDROW-HOFF LEARNING ALGORITHM

$m$

1.  $net = \sum_{i=1}^m w_i x_i$
2. Using a linear activation function  $y = f(net) = net$

3. The error between the network output and the desired output is:

$$e = \frac{1}{2}(d - y)^2$$

4. Using the chain rule, the derivative w.r.t. weights is:

$$\frac{de}{dw} = \frac{de}{dy} \frac{dy}{dw} = -(d - y)x$$

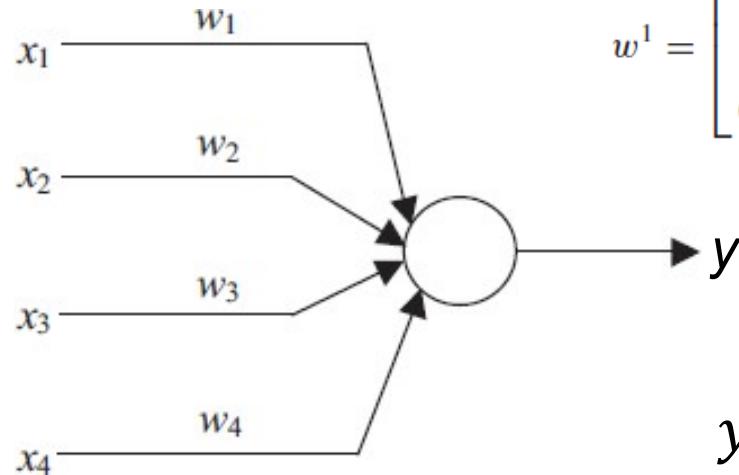
5. Update the weights using steepest descent:

$$w = w - \alpha \frac{\partial e}{\partial w_i}$$

Define  $\Delta w = -\frac{\alpha \partial e}{\partial w_i}$  then  $w = w + \Delta w$



# EXAMPLE



$$w^1 = \begin{bmatrix} 1 \\ -1 \\ 0 \\ 0.5 \end{bmatrix}, x^1 = \begin{bmatrix} 1 \\ -2 \\ 1.5 \\ 0 \end{bmatrix}, x^2 = \begin{bmatrix} 1 \\ -0.5 \\ -2 \\ -1.5 \end{bmatrix} \text{ and } x^3 = \begin{bmatrix} 0 \\ 1 \\ -1 \\ 1.5 \end{bmatrix}$$

Desired output,  $d = [1 \ -1 \ 0]$

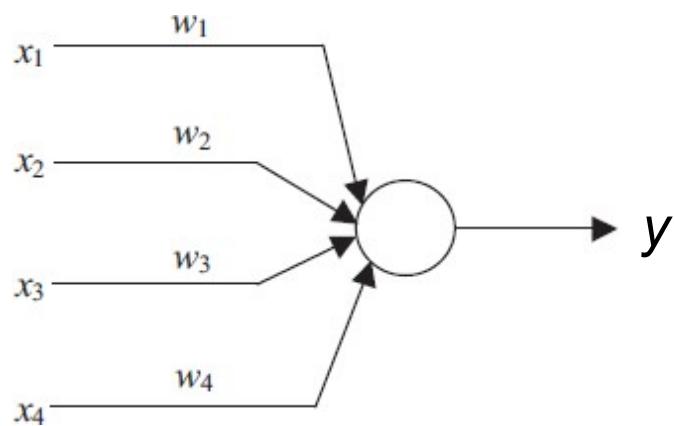
$$y = f(\text{net}) = \text{net}$$

Use **Widrow-Hoff** learning to update the weights

Let  $\alpha = 1$



# EXAMPLE



$$w^1 = \begin{bmatrix} 1 \\ -1 \\ 0 \\ 0.5 \end{bmatrix}, x^1 = \begin{bmatrix} 1 \\ -2 \\ 1.5 \\ 0 \end{bmatrix}, x^2 = \begin{bmatrix} 1 \\ -0.5 \\ -2 \\ -1.5 \end{bmatrix} \text{ and } x^3 = \begin{bmatrix} 0 \\ 1 \\ -1 \\ 1.5 \end{bmatrix}$$

Desired output,  $d = [1 \ -1 \ 0]$

## Iteration One

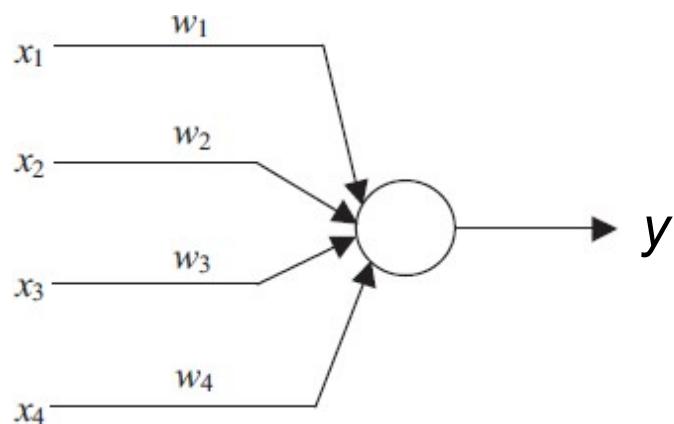
$$net^1 = w^1 x^1 = [1 \ -1 \ 0 \ .5] \begin{bmatrix} 1 \\ -2 \\ 1.5 \\ 0 \end{bmatrix} = 3 \rightarrow y = 3$$

$$\Delta w^1 = \alpha (d^1 - y^1) x^1 = 1 * (1 - 3) \begin{bmatrix} 1 \\ -2 \\ 1.5 \\ 0 \end{bmatrix} = \begin{bmatrix} -2 \\ 4 \\ -3 \\ 0 \end{bmatrix}$$

$$w^2 = w^1 + \Delta w^1 = \begin{bmatrix} 1 \\ -1 \\ 0 \\ 0.5 \end{bmatrix} + \begin{bmatrix} -2 \\ 4 \\ -3 \\ 0 \end{bmatrix} = \begin{bmatrix} -1 \\ 3 \\ -3 \\ 0.5 \end{bmatrix}$$



# EXAMPLE



$$w^1 = \begin{bmatrix} 1 \\ -1 \\ 0 \\ 0.5 \end{bmatrix}, x^1 = \begin{bmatrix} 1 \\ -2 \\ 1.5 \\ 0 \end{bmatrix}, x^2 = \begin{bmatrix} 1 \\ -0.5 \\ -2 \\ -1.5 \end{bmatrix} \text{ and } x^3 = \begin{bmatrix} 0 \\ 1 \\ -1 \\ 1.5 \end{bmatrix}$$

Desired output,  $d = [1 \ -1 \ 0]$

## Iteration Two

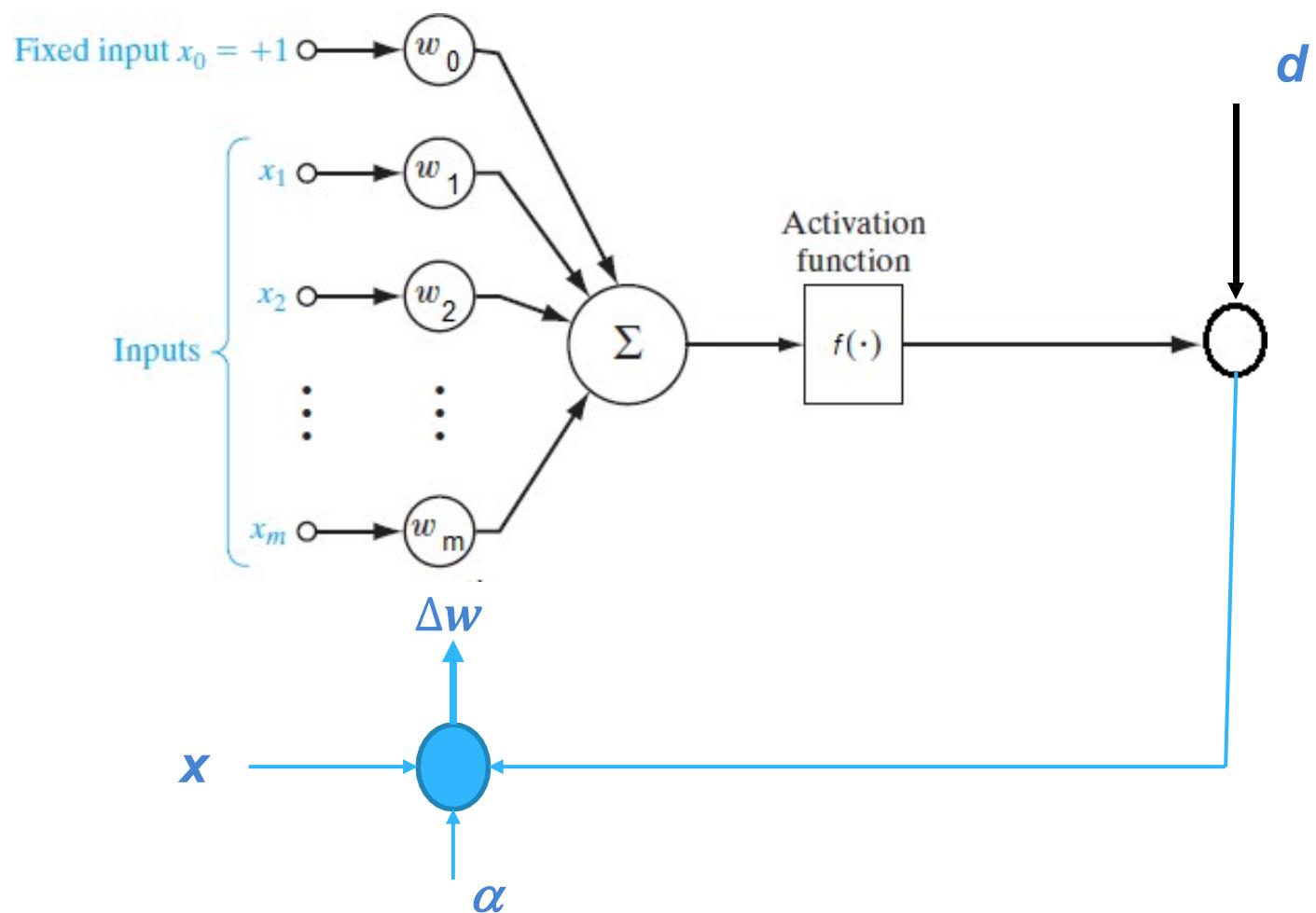
$$net^2 = [-1 \ 3 \ -3 \ 0.5] \begin{bmatrix} 1 \\ -0.5 \\ -2 \\ -1.5 \end{bmatrix} = 2.75 \Rightarrow y^2 = 2.75$$

$$\Delta w^2 = \alpha(d^2 - y^2)x^2 = 1 (-1 - 2.75) \begin{bmatrix} 1 \\ -0.5 \\ -2 \\ -1.5 \end{bmatrix} = \begin{bmatrix} -3.75 \\ 1.875 \\ 7.5 \\ 5.62 \end{bmatrix}$$

$$w^3 = w^2 + \Delta w^2 = \begin{bmatrix} -1 \\ 3 \\ -3 \\ 0.5 \end{bmatrix} + \begin{bmatrix} -3.75 \\ 1.875 \\ 7.5 \\ 5.62 \end{bmatrix}$$



# DELTA RULE LEARNING



# DELTA RULE LEARNING: SINGLE NEURON

$$net = w^T x$$

Using a linear activation function  $y = f(net)$

The error between the network output and the desired output is

$$E = \frac{1}{2}(d - y)^2$$

The derivative w.r.t. weights is

$$\frac{dE}{dw_i} = \frac{dE}{dy} \frac{dy}{dw_i} = -(d - y) f'(net) x_i$$

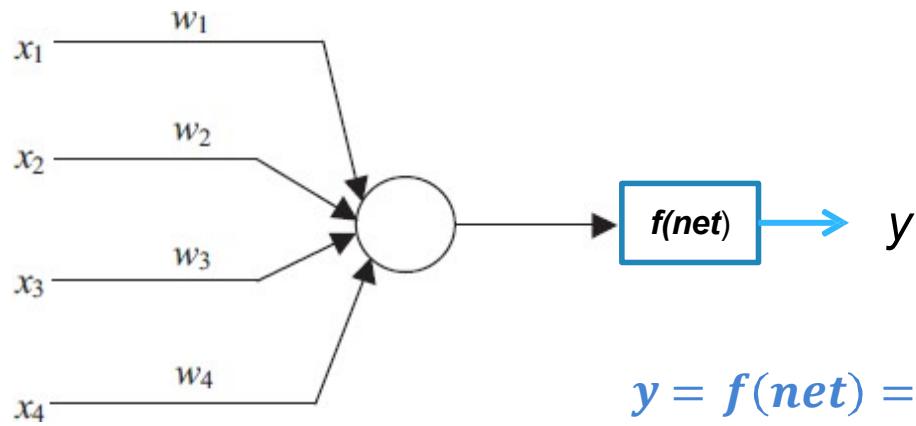
Update the weights using delta rule

$$w_i = w_i - \alpha \frac{dE}{dw_i}$$

In vector format:  $W = W - \alpha \nabla E$



# EXAMPLE



$$y = f(\text{net}) = \frac{1 - e^{-\text{net}}}{1 + e^{-\text{net}}}$$

$$\text{Note: } y' = 0.5(1 - y^2)$$

$$w^1 = \begin{bmatrix} 1 \\ -1 \\ 0 \\ 0.5 \end{bmatrix}, x^1 = \begin{bmatrix} 1 \\ -2 \\ 0 \\ -1 \end{bmatrix}, x^2 = \begin{bmatrix} 0 \\ 1.5 \\ -0.5 \\ -1 \end{bmatrix} \text{ and } x^3 = \begin{bmatrix} -1 \\ 1 \\ 0.5 \\ -1 \end{bmatrix}$$

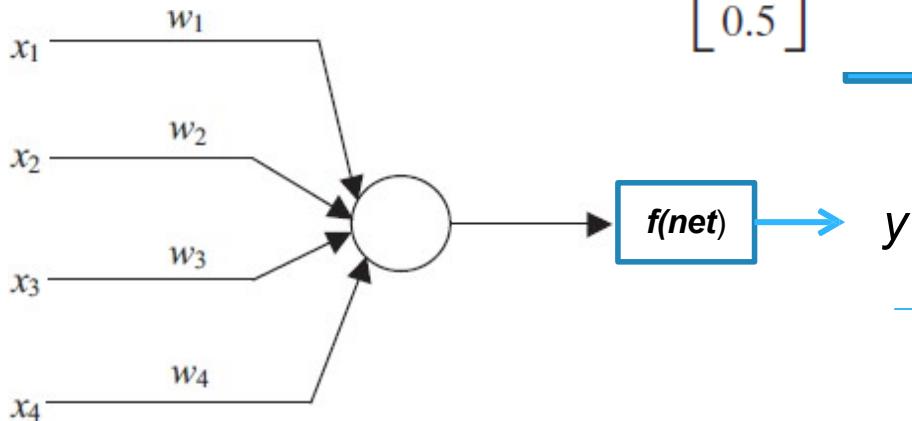
Desired output,  $d = [-1 \ -1 \ 1]$

Use **Delta Rule** learning to update the weights

with  $\alpha = 0.1$



# EXAMPLE



$$w^1 = \begin{bmatrix} 1 \\ -1 \\ 0 \\ 0.5 \end{bmatrix}, x^1 = \begin{bmatrix} 1 \\ -2 \\ 0 \\ -1 \end{bmatrix}, x^2 = \begin{bmatrix} 0 \\ 1.5 \\ -0.5 \\ -1 \end{bmatrix} \text{ and } x^3 = \begin{bmatrix} -1 \\ 1 \\ 0.5 \\ -1 \end{bmatrix}$$

Desired output,  $d = [-1 \ -1 \ 1]$

**Iteration One  
Pattern One**

$$\text{net} = w^T x = [1 \ -1 \ 0 \ 0.5] \begin{bmatrix} 1 \\ -2 \\ 0 \\ -1 \end{bmatrix} = 2.5$$

$$y = \frac{1 - e^{-\text{net}}}{1 + e^{-\text{net}}} \Rightarrow y = 0.848$$

$$y' = 0.5(1 - y^2) = 0.140$$

$$\nabla E = -\alpha(d - y)y'x$$

$$= -0.1(-1 - 0.848)(0.14) \begin{bmatrix} 1 \\ -2 \\ 0 \\ -1 \end{bmatrix}$$

$$= 0.0259 \begin{bmatrix} 1 \\ -2 \\ 0 \\ -1 \end{bmatrix} = \begin{bmatrix} 0.0259 \\ -0.0518 \\ 0 \\ -0.0259 \end{bmatrix}$$

$$w = w - \nabla E = \begin{bmatrix} 1 \\ -1 \\ 0 \\ 0.5 \end{bmatrix} - \begin{bmatrix} 0.0259 \\ -0.0518 \\ 0 \\ -0.0259 \end{bmatrix} = \begin{bmatrix} 0.9741 \\ -0.9482 \\ 0 \\ 0.5259 \end{bmatrix}$$

# EXAMPLE

$$w^1 = \begin{bmatrix} 1 \\ -1 \\ 0 \\ 0.5 \end{bmatrix}, x^1 = \begin{bmatrix} 1 \\ -2 \\ 0 \\ -1 \end{bmatrix}, x^2 = \begin{bmatrix} 0 \\ 1.5 \\ -0.5 \\ -1 \end{bmatrix} \text{ and } x^3 = \begin{bmatrix} -1 \\ 1 \\ 0.5 \\ -1 \end{bmatrix}$$

Desired output,  $d = [-1 \textcolor{blue}{-1} 1]$

## Pattern Two

$$net = w^T x$$

$$= [0.974 \quad -0.948 \quad 0 \quad 0.5259] \begin{bmatrix} 0 \\ 1.5 \\ -0.5 \\ -1 \end{bmatrix} \\ = -1.948$$

$$y = \frac{1 - e^{-net}}{1 + e^{-net}} \Rightarrow y = -0.7505$$

$$y' = 0.5(1 - y^2) = 0.2184$$

$$\nabla E = -\alpha(d - y) y' x$$

$$= -0.1(-1 + 0.7505)(0.2184) \begin{bmatrix} 0 \\ 1.5 \\ -0.5 \\ -1 \end{bmatrix} \\ = \begin{bmatrix} 0 \\ 0.0082 \\ -0.0027 \\ -0.0054 \end{bmatrix}$$

$$w = w - \nabla E = \begin{bmatrix} 0.974 \\ -0.948 \\ 0 \\ 0.5259 \end{bmatrix} - \begin{bmatrix} 0 \\ 0.0082 \\ -0.0027 \\ -0.0054 \end{bmatrix} = \begin{bmatrix} 0.9741 \\ -0.9563 \\ 0.0027 \\ \textcolor{blue}{0.5314} \end{bmatrix}$$

# EXAMPLE

Iteration One

- Pattern One
- Pattern Two
- Pattern Three

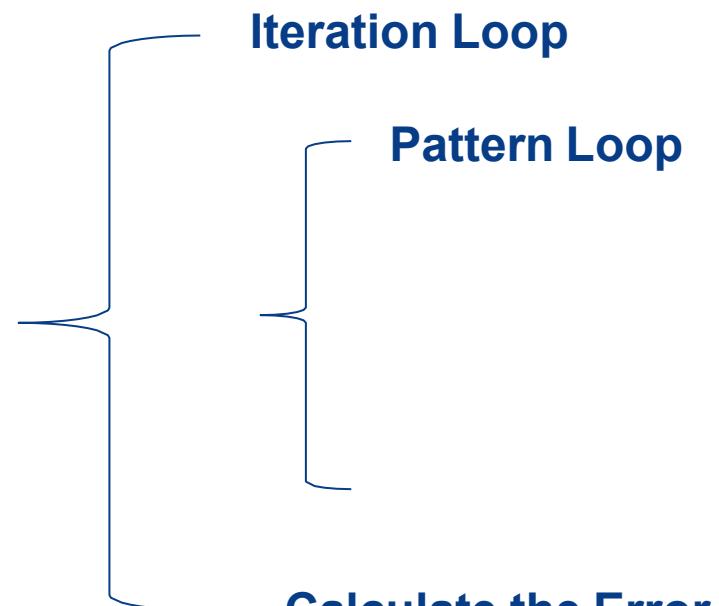
Iteration Two

- Pattern One
- Pattern Two
- Pattern Three

Iteration Three

- Pattern One
- Pattern Two
- Pattern Three

Two Loops



...



# MATLAB CODE

- % Delta Rule Example for single neuron

- $w = [1 \ -1 \ 0 \ 0.5]'$ ;

- $x1 = [1 \ -2 \ 0 \ -1]'$ ;  $x2 = [0 \ 1.5 \ -0.5 \ -1]'$ ;  $x3 = [-1 \ 1 \ 0.5 \ -1]'$ ;  $d1 = -1$ ;  $d2 = -1$ ;  
 $d3 = 1$ ;

- $a = 0.1$ ;

- **for iter = 1:100**

- % Pattern 1

- $net = w' * x1$ ;

- $y1 = (1 - \exp(-net)) / (1 + \exp(-net))$ ;  $yp = 0.5 * (1 - y1^2)$ ;

- $dE = -a * (d1 - y1) * yp * x1$ ;

- $w = w - dE$ ;

- % Pattern 2

- $net = w' * x2$ ;

- $y2 = (1 - \exp(-net)) / (1 + \exp(-net))$ ;  $yp = 0.5 * (1 - y2^2)$ ;

- $dE = -a * (d2 - y2) * yp * x2$ ;

- $w = w - dE$ ;

**% Pattern 3**

```
net = w'*x3;
y3 = ( 1 - exp(-net) ) / ( 1 + exp(-net) );
yp = 0.5 * ( 1 - y3^2);
dE = -a * (d3 - y3)*yp*x3;
w = w - dE;
```

$Err(iter) = (d1-y1)^2 + (d2-y2)^2 + (d3-y3)^2$ ;

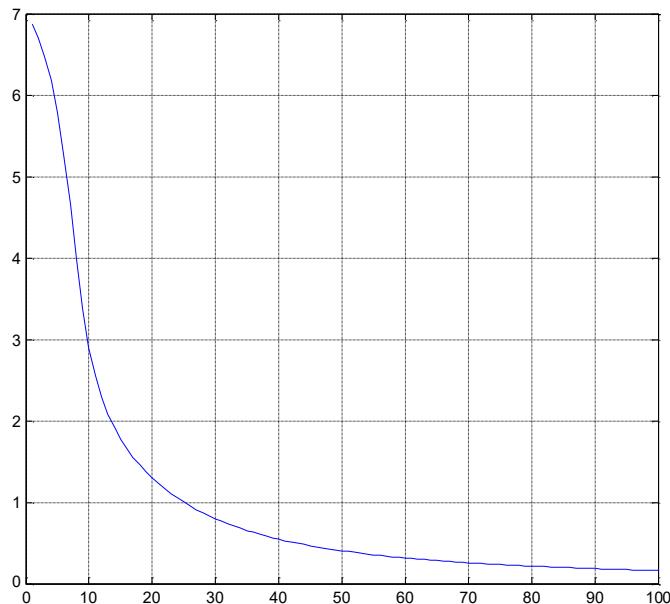
**End**

`plot(Err); grid`



# MATLAB RESULTS

$$\alpha = 0.1$$

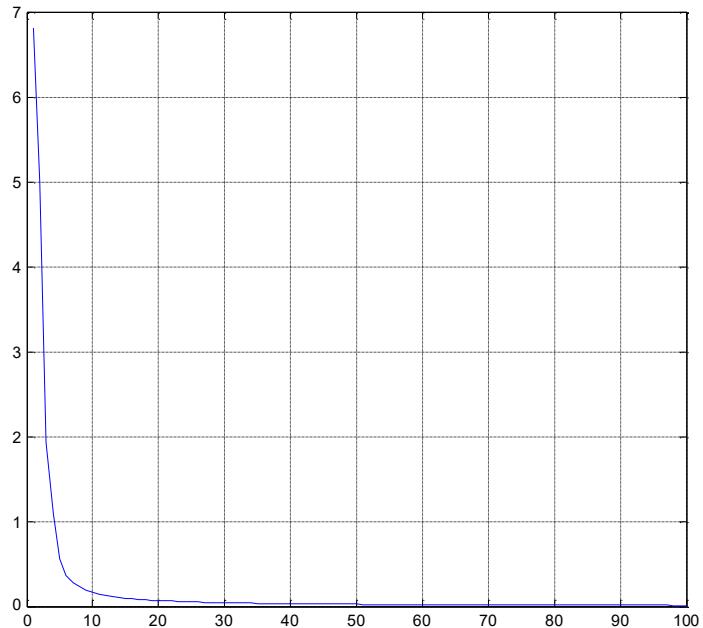


$$y_1 = -0.8897$$

$$y_2 = -0.7191$$

$$y_3 = 0.7319$$

$$\alpha = 0.9$$



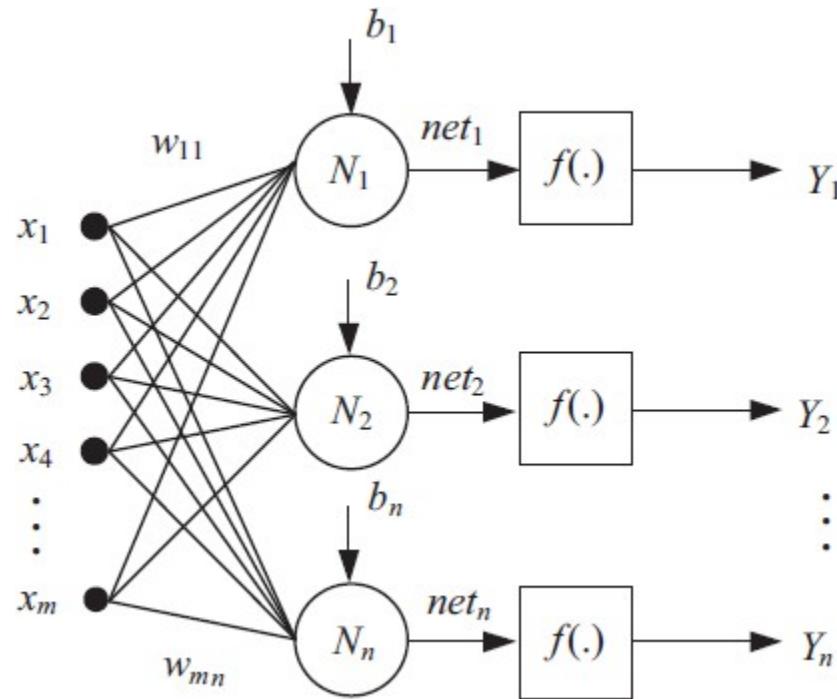
$$y_1 = -0.9669$$

$$y_2 = -0.9240$$

$$y_3 = 0.9278$$



# MULTI-NEURONS



$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix} \quad W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & \\ \vdots & \vdots & \ddots & \vdots \\ w_{m1} & w_{m2} & \cdots & w_{mn} \end{bmatrix} \quad b = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix} \quad Y = f(W^T x + b)$$



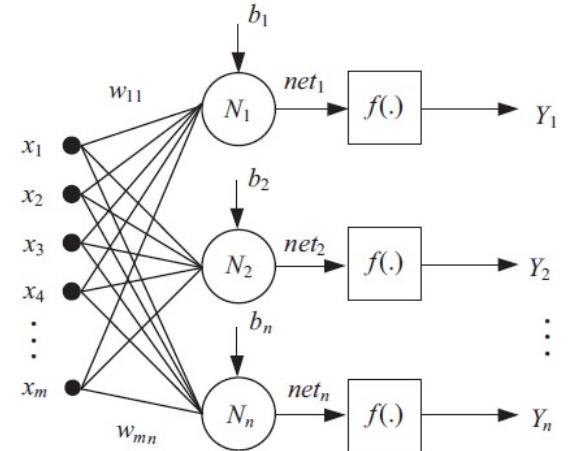
# DELTA RULE LEARNING: MULTI-NEURONS

For each output neuron  $j = 1 : m$

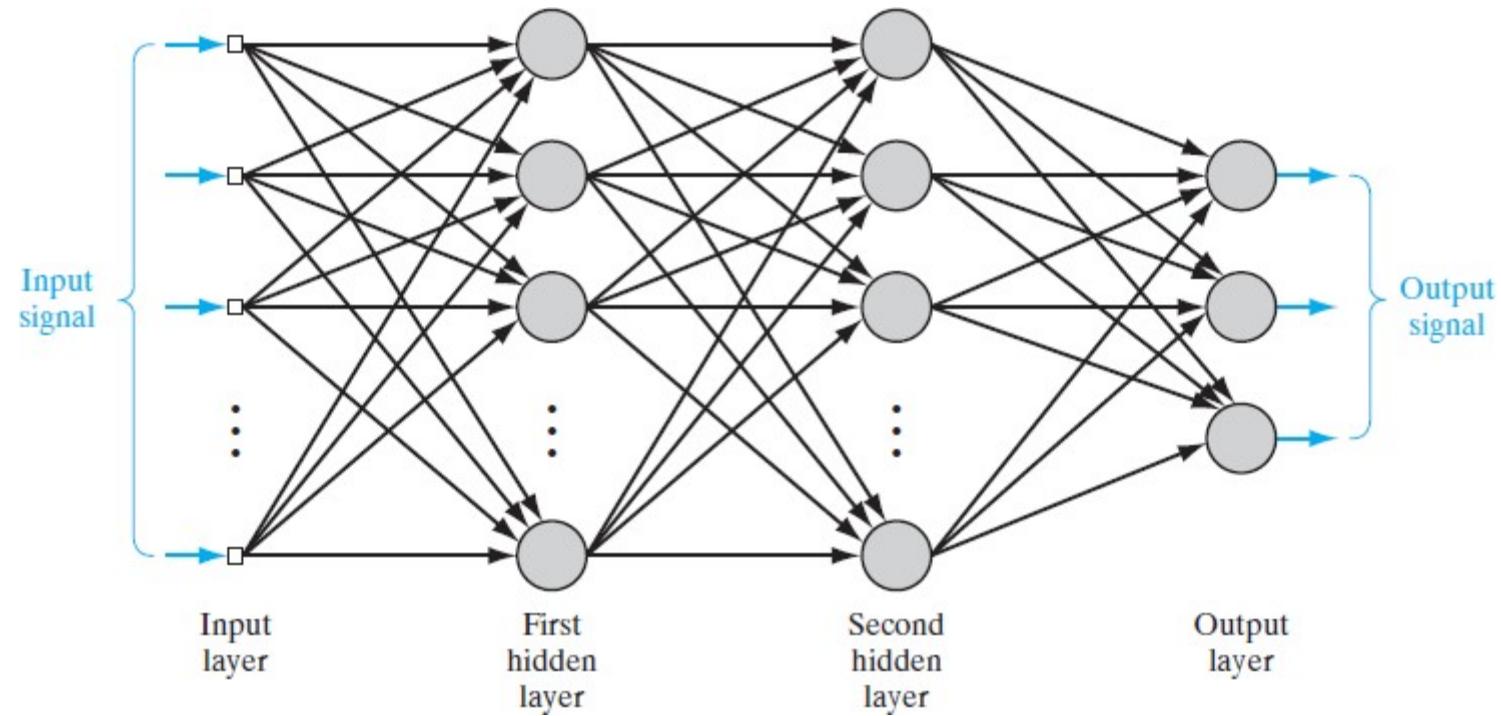
$$\begin{aligned} & m \\ \text{net}_j &= \sum_{i=1}^m w_{ij} x_i \\ y_j &= f(\text{net}_j) \end{aligned}$$

$$\frac{dE}{dw_{ij}} = -(d_j - y_j) f'(\text{net}_j) x_i$$

$$w_{ij} = w_{ij} - \alpha \frac{dE}{dw_{ij}}$$



# MULTILAYER FEEDFORWARD NETWORK



# CONCLUSIONS

- Widrow-Hoff learning algorithm is a simple supervised learning algorithm used for Perceptron
- The weight change at each iteration by minimizing an error function between the perceptron output and the desired output
- Steepest descent algorithms are iterative procedures that are used to find the minimum of functions.
- These algorithms update the variables in the direction of the negative derivative (for single variable) or gradient (for multi-variables)

